Atmospheric Passive Remote Sensing

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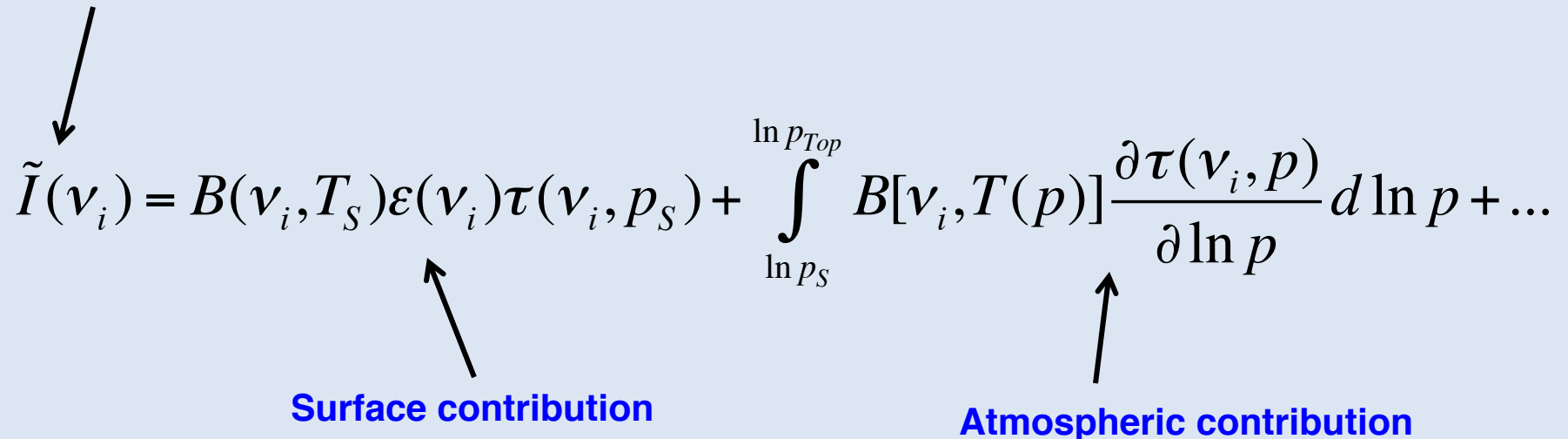**August 30, 2018**

What is Passive Remote Sensing?

Really, what is passive remote sensing?

- **Remotely measured electromagnetic radiation where**
    - **<u>the source is not controlled</u>.**

- **Examples:**
    - **Visible and infrared imaging.**
    - **Backscattered solar ultraviolet.**
    - **Microwave and infrared emission spectra.**
    - **Solar occultation spectra.**

- **Two general types of space-based remote sensing:**
    - **Nadir (downward looking).**
    - **Limb-viewing.**

- ***<u>Atmospheric</u> remote sensing often means inferring vertical structure, called 'remote sounding'.***

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The Fundamental Approach:
Use the Radiative Transfer Equation to Understand the Atmosphere

- We know *observed* radiance.

- We *want* internal information like T_s, $T(p)$, etc.

Observed outgoing radiance

$$\tilde{I}(\nu_i) = B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) + \int_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)]\frac{\partial \tau(\nu_i, p)}{\partial \ln p} d\ln p + ...$$

Surface contribution

Atmospheric contribution

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Two Basic Aspects of Remote Sounding

1. *The forward problem:* given a known internal state (surface, atmosphere, clouds), what is the emitted radiance?

2. *The retrieval or inverse problem:* what internal state explains observed radiances? (Impossible without a forward model.)

Inverse problems are found in many branches of geophysics, astrophysics, and medicine. Most infer physical state from propagating waves.

A Nadir Sounding Example:
The AIRS/AMSU Suite

AIRS = Atmospheric Infrared Sounder
AMSU = Advanced Microwave Sounding Unit
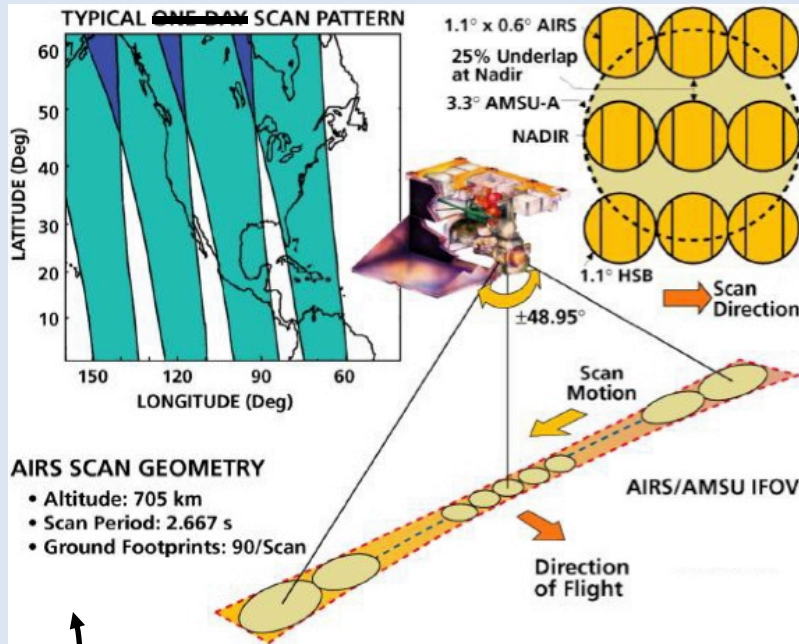
1. **AMSU footprint, 45 km across at nadir, contains 9 AIRS spectra**
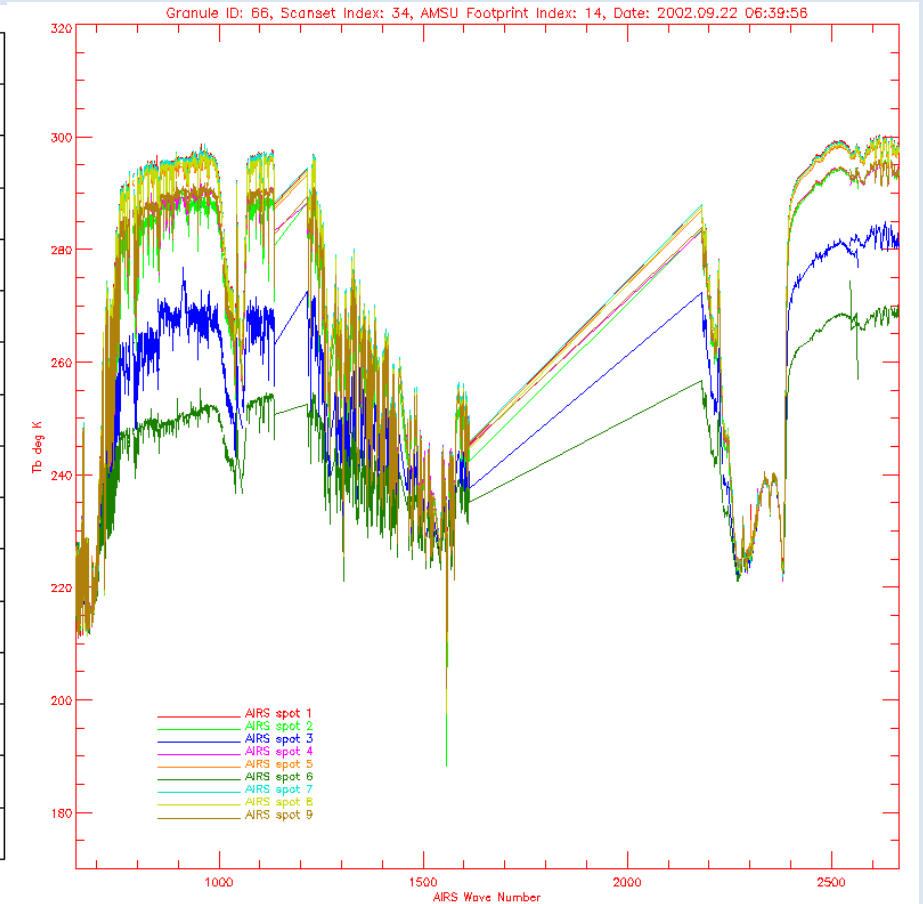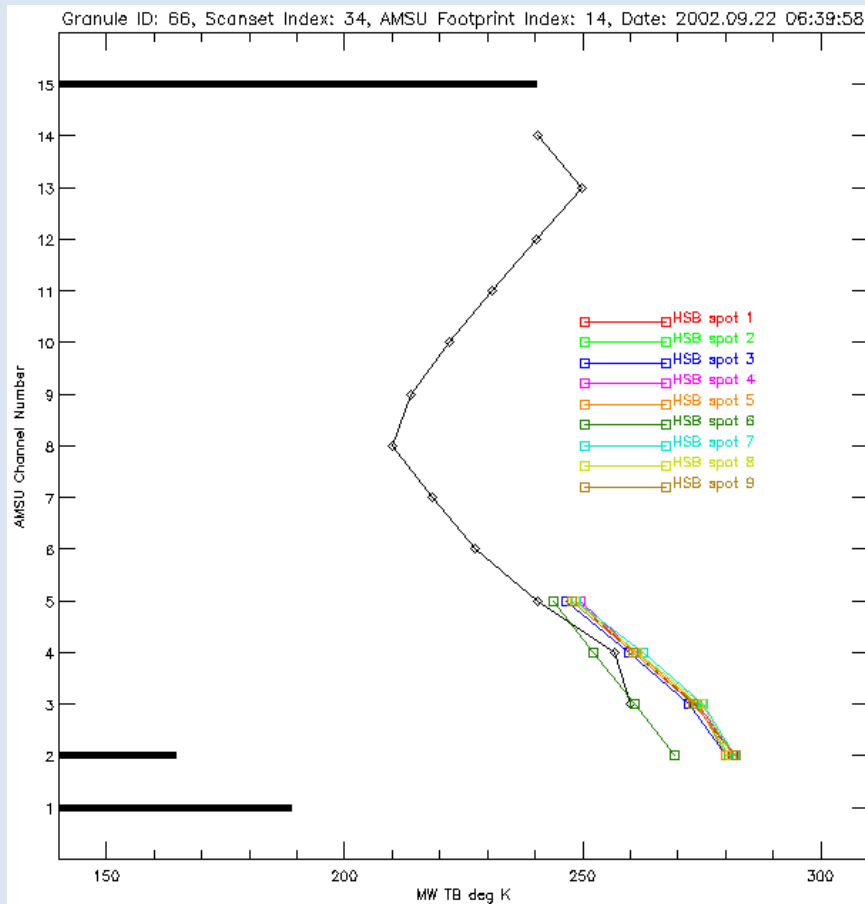   – **THIS IS THE RETRIEVAL GRANULARITY.**

2. **Viewing swath 30 AMSU footprints or ~1650 km wide.**

3. **The result: 324,000 retrievals per day (over a 15 year record).**

One Set of AIRS Suite Spectra in the Atlantic
We now have about 10^9 in a sixteen year record
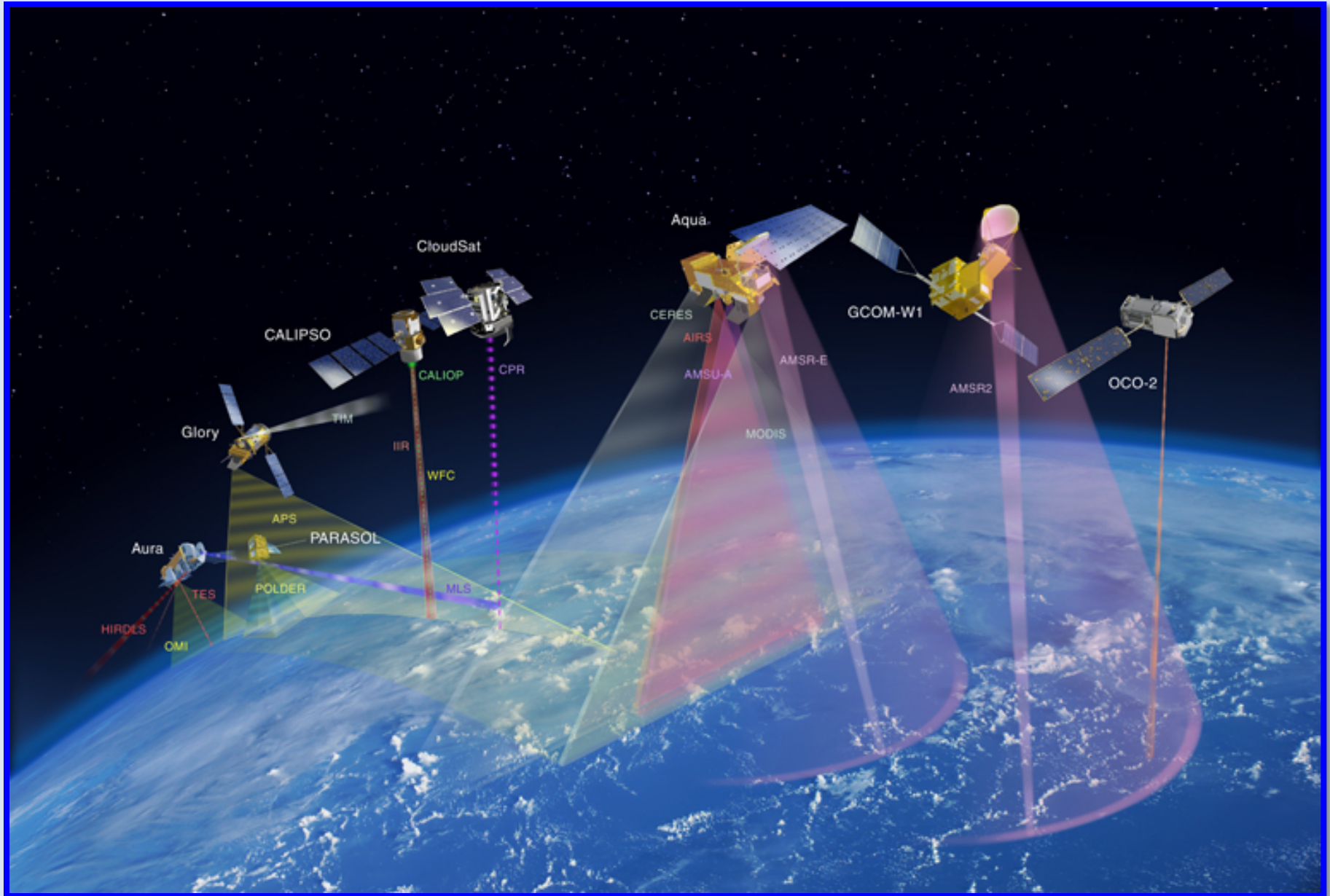## (about 10^{10} IR spectra)

22 Sep 2002, 0630 UT, night time near 25 N and 73 W

1 AMSU, 9 ~~HSB~~ Spectra

9 AIRS Spectra

AIRS is One Example from the A-Train:
An international commitment to climate science

About Retrieved Quantities

Retrieved quantities are inferences (<u>estimates</u>) of the true state of the atmosphere.

Some basic challenges:

1. **Developing a reliable forward model.**
    –   **This usually means detailed spectroscopic knowledge.**

2. **Implementing a retrieval algorithm.**

3. **'Validation' of retrievals against other measurements.**

4. **Interpretation of resulting very large data sets.**

One Set of AIRS Suite Spectra in the Atlantic
We now have about 10^9 in a sixteen year record (about 10^{10} IR spectra)

22 Sep 2002, 0630 UT, night time near 25 N and 73 W
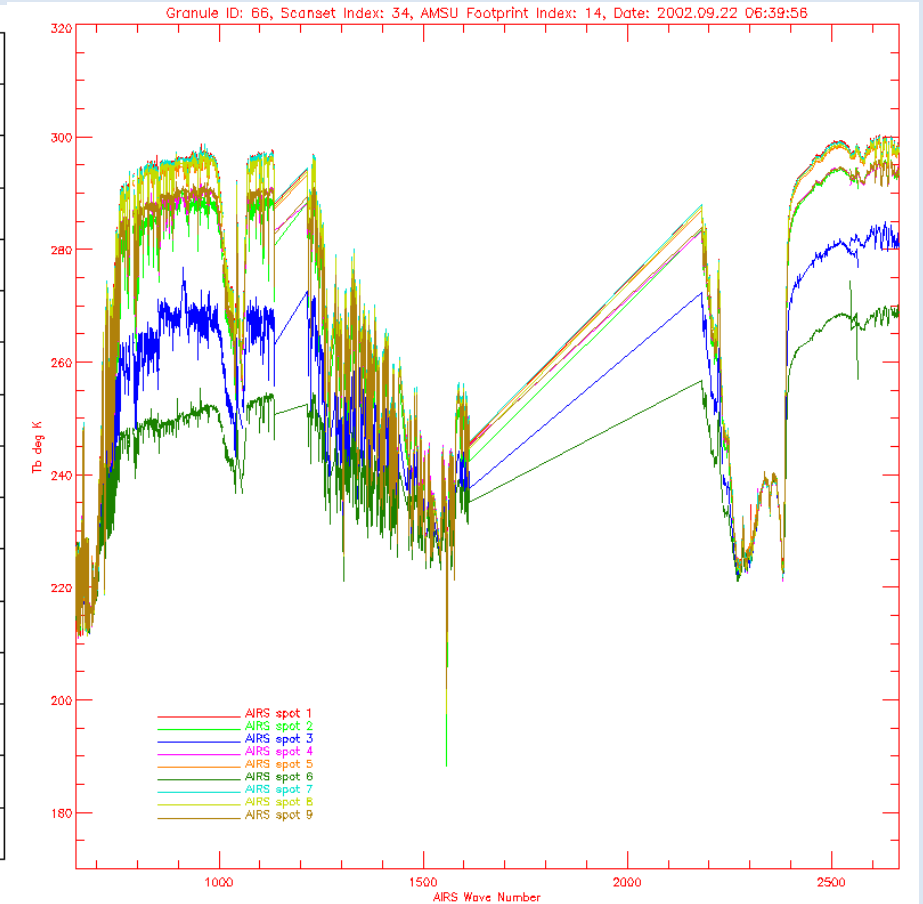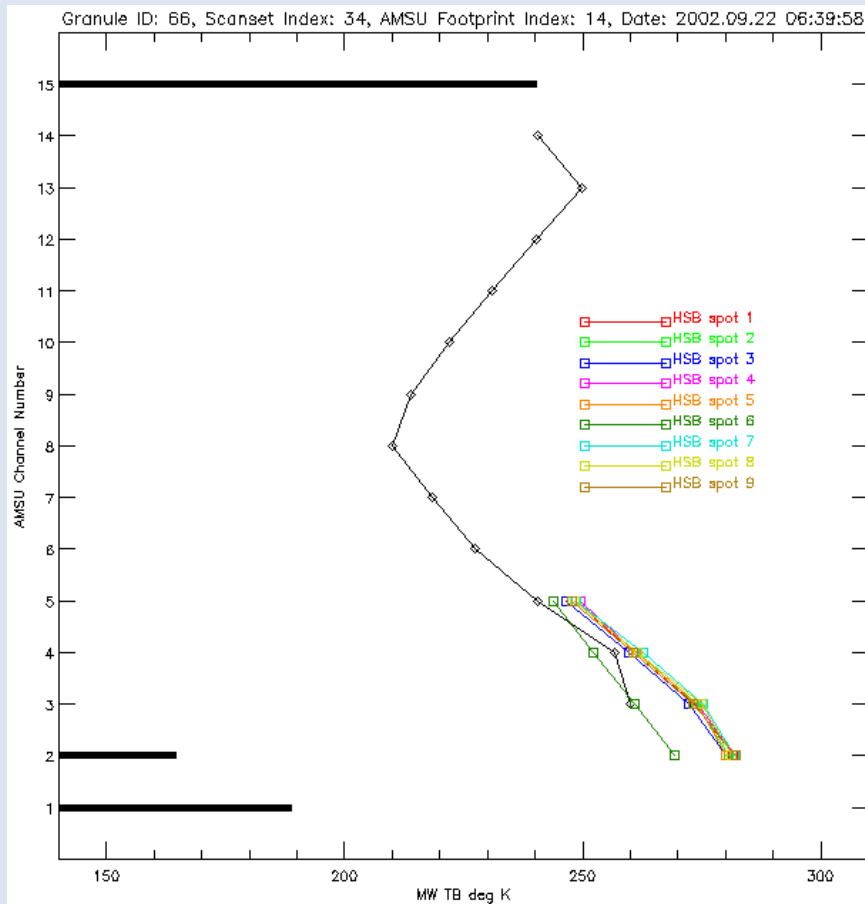
1 AMSU, 9 ~~HSB~~ Spectra

9 AIRS Spectra

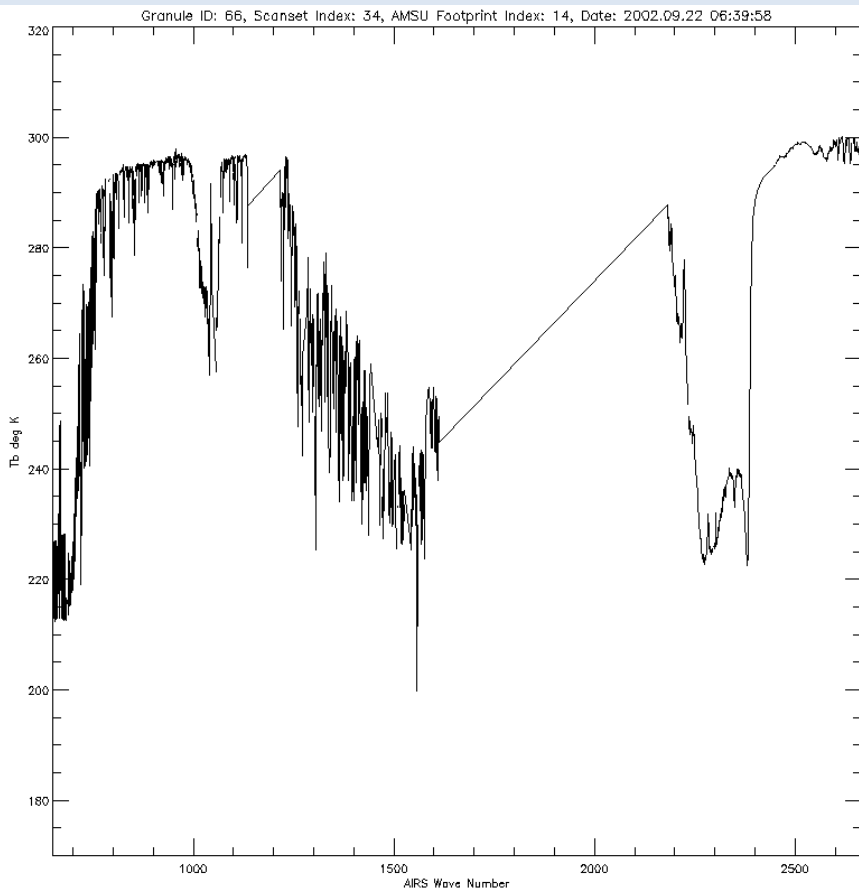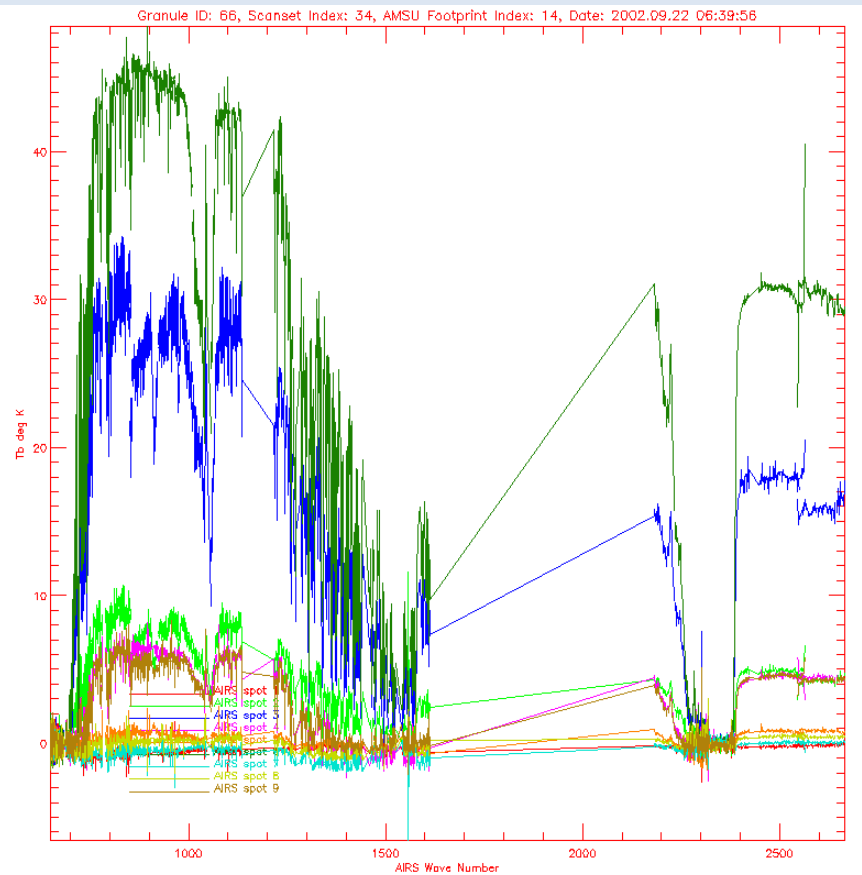# *Retrieved* Cloud-Cleared Spectrum
and differences from radiances in previous slide

1 Cloud-Cleared Spectrum

CC Spectrum – 9 AIRS Spectra

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Retrieved Geophysical Quantities
(from the cloud cleared radiances just shown)
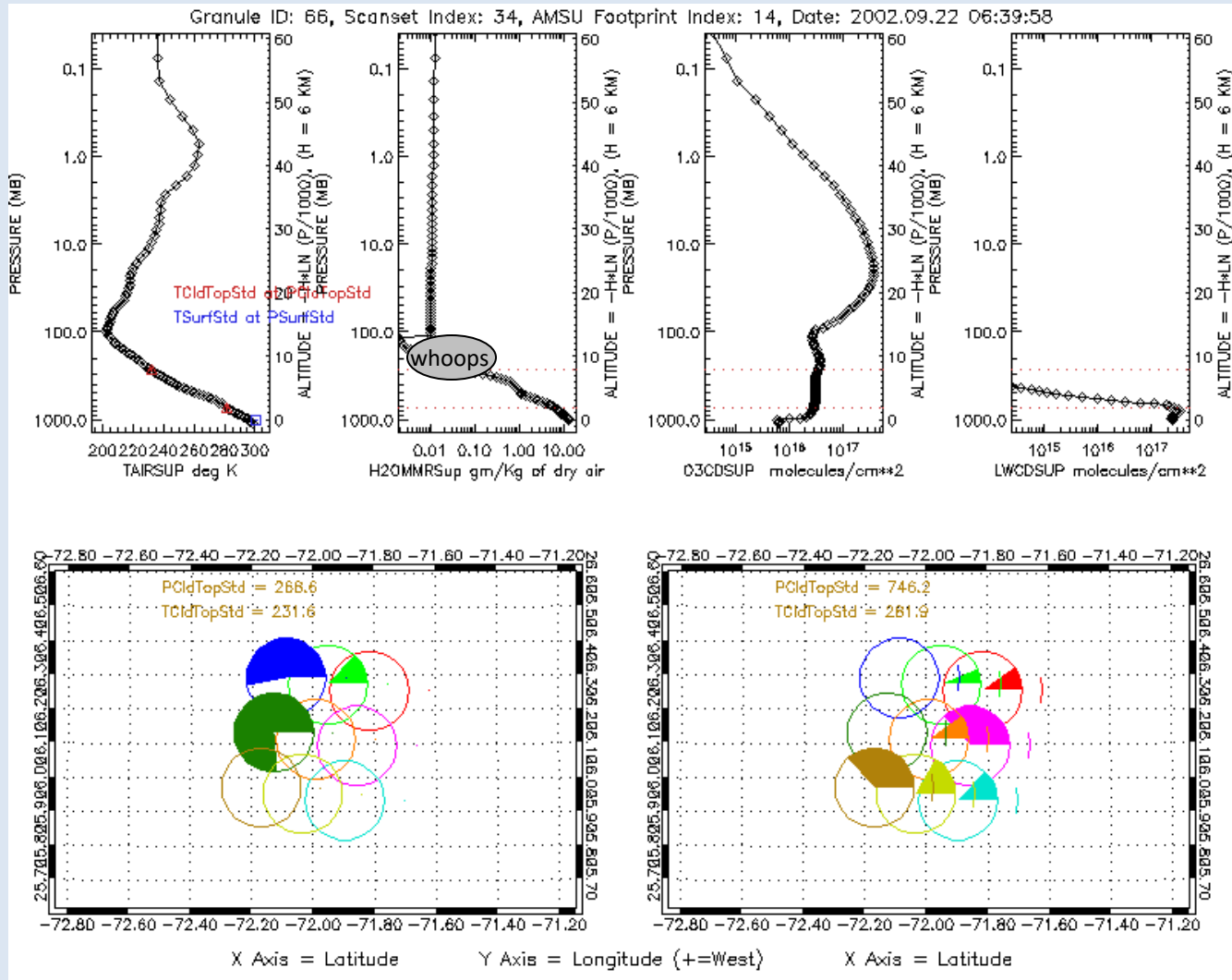
The Radiative Transfer Equation and Weighting Functions

Weighting functions relate internal state and calculated outgoing radiance

Observed radiance

$$\tilde{I}(\nu_i) = B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) + \int_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)]\frac{\partial \tau(\nu_i, p)}{\partial \ln p}\, d\ln p + ...$$

Surface contribution

Atmospheric contribution

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Nadir Weighting Functions
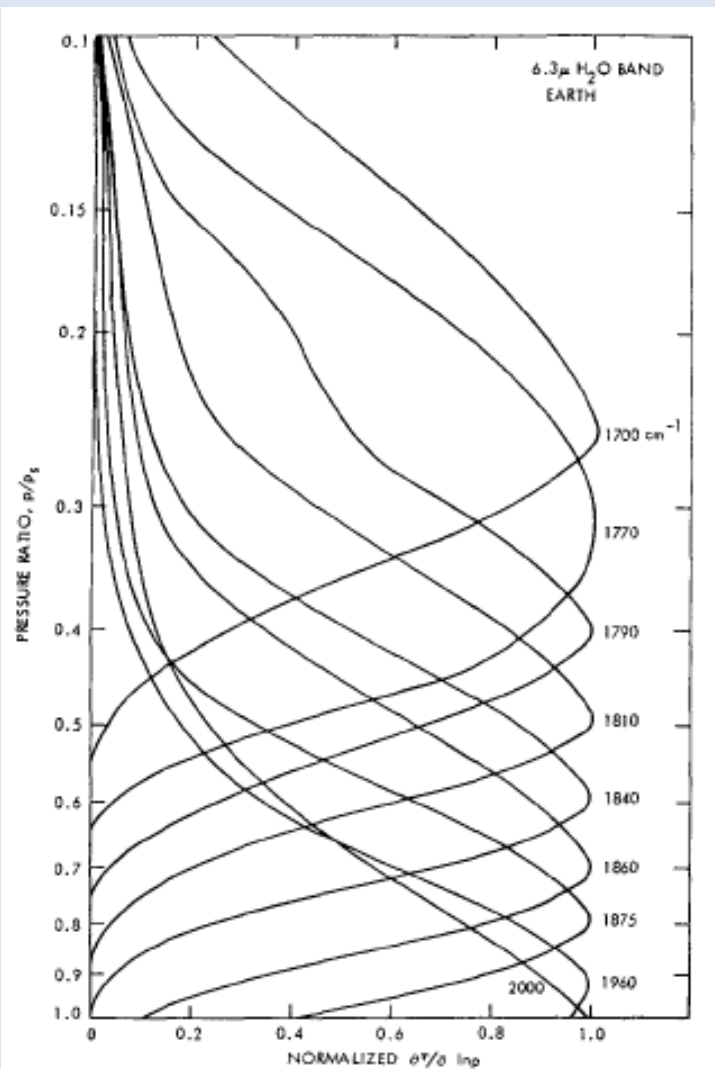
FIG. 1. Normalized weighting functions $(d\tau/d \ln p)$ for the selected set of nine sounding frequencies computed for an instrumental slit function of 5 cm^{-1} (see text).

$$\frac{\partial \tau(\nu_i, p)}{\partial \ln p}$$

Weighting Function = Vertical Derivative of Optical Depth

The functions show the contribution an altitude makes to calculated radiance.

Also called:

- **Adjoints**

- **Jacobians**

Note: *Fine scale structure is retrieved by deconvolving weighting functions.*

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Chahine, 1970.

Limb Viewing Geometry and Weighting Functions

Fig. 1. Limb experiment geometry.

2. Limb experiment vertical ozone weighting functions in the 9.6-μm band at selected tangent heights.

Limb Viewing Characteristics

Good:
- **The limb is viewed against cold space**
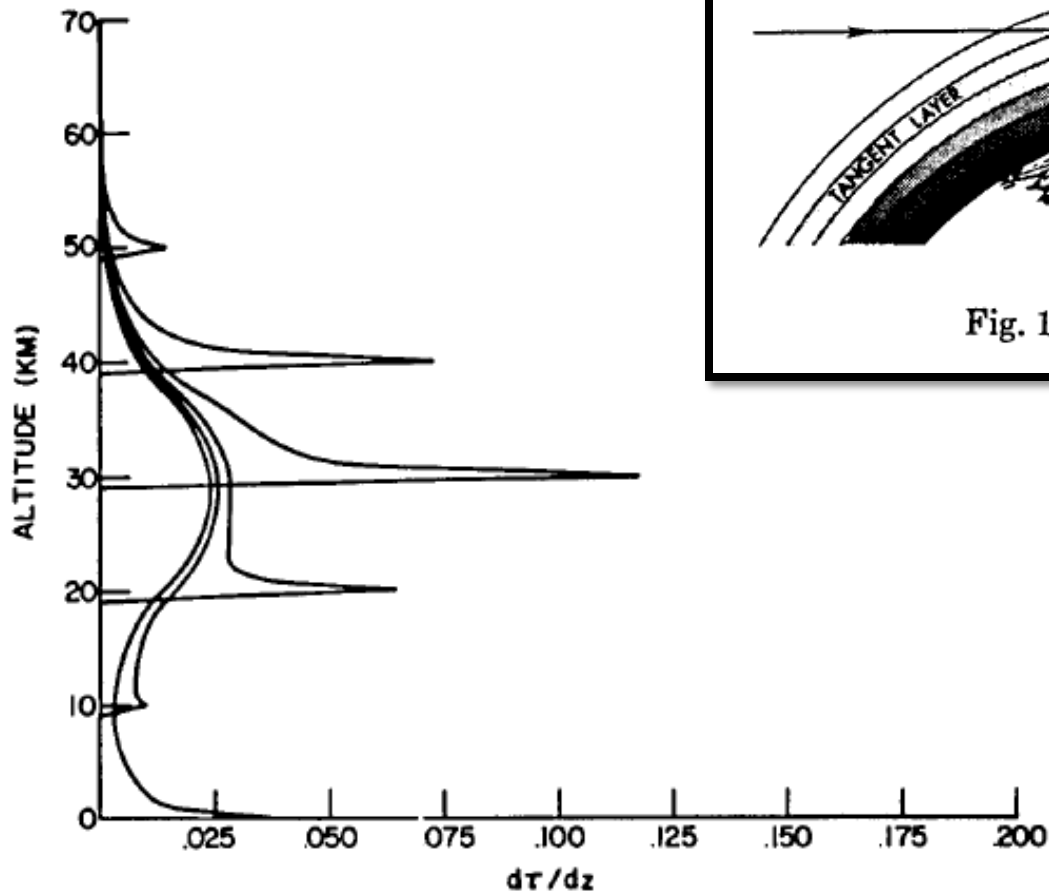 - **high signal-to-noise**
  - **no surface term in the retrieval.**
- **Very sharp weighting functions**
  - **give high vertical resolution.**

Not so good:
- **Very sensitive to clouds.**
  - **Makes limb sounding most useful in middle troposphere and up.**

Note: **GPS limb occultations can be inverted to stable, very high resolution, cloud-free profiles.** *But, not a passive technique, also temperature-water vapor ambiguity for T > 250 K.*

How Much Information?
Retrieval algorithms extract the information content of spectra.

22 Sep 2002, 0630 UT, night time near 25 N and 73 W

1 AMSU, 9 ~~HSB~~ Spectra

9 AIRS Spectra
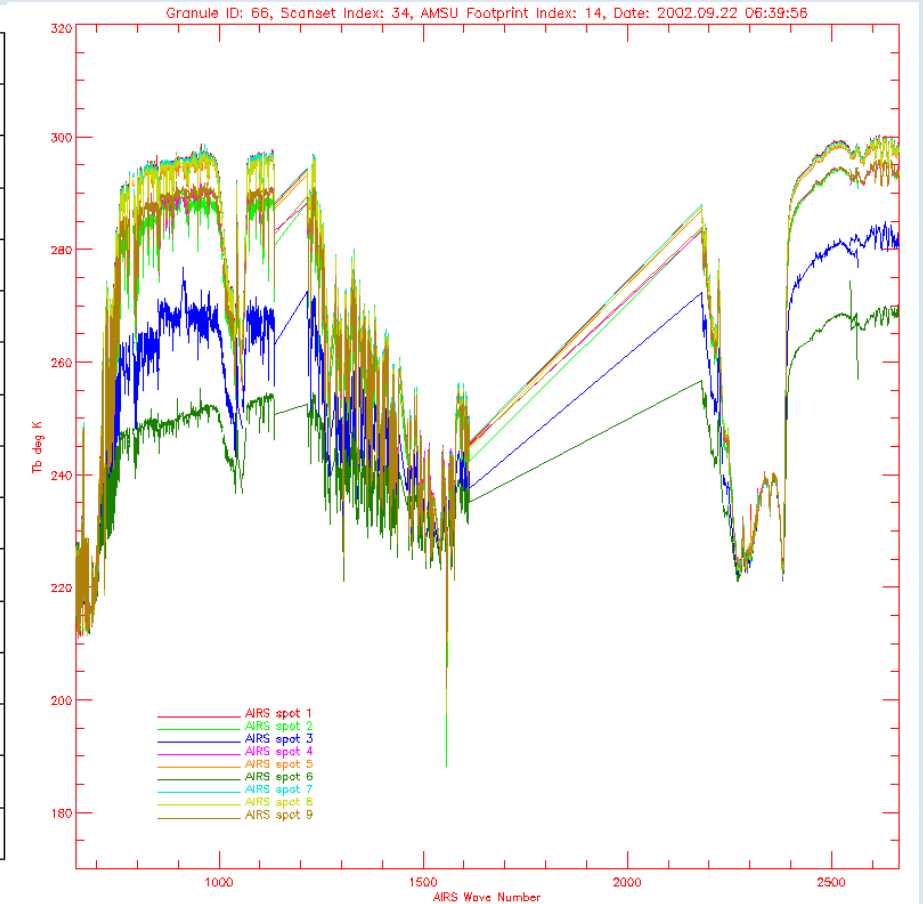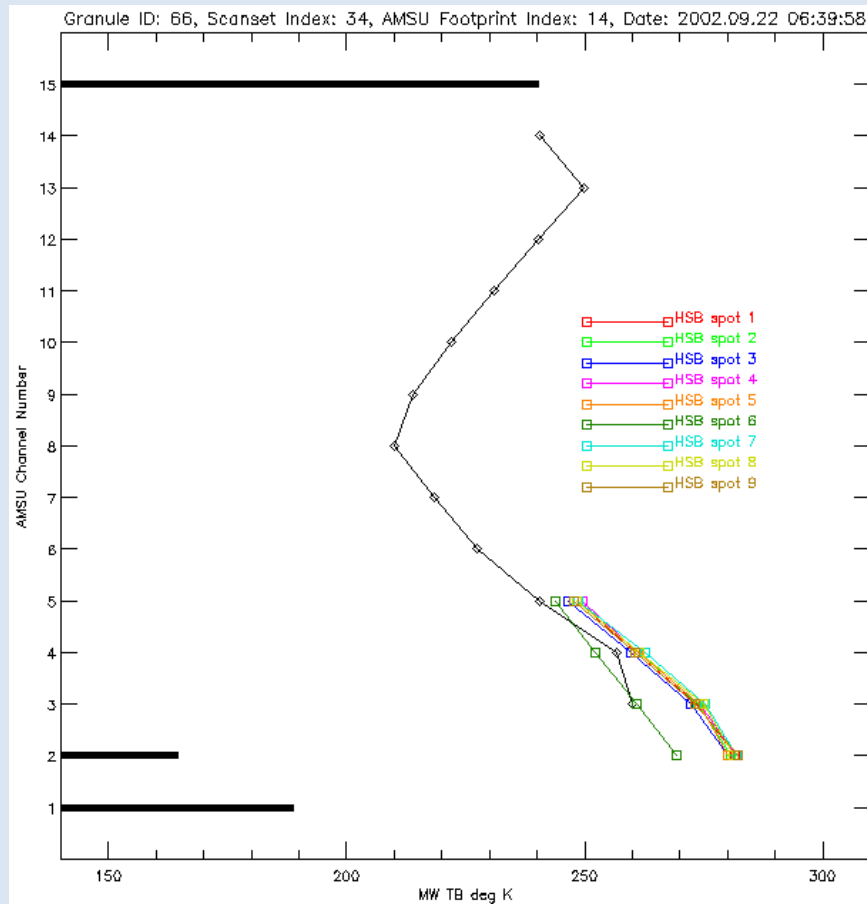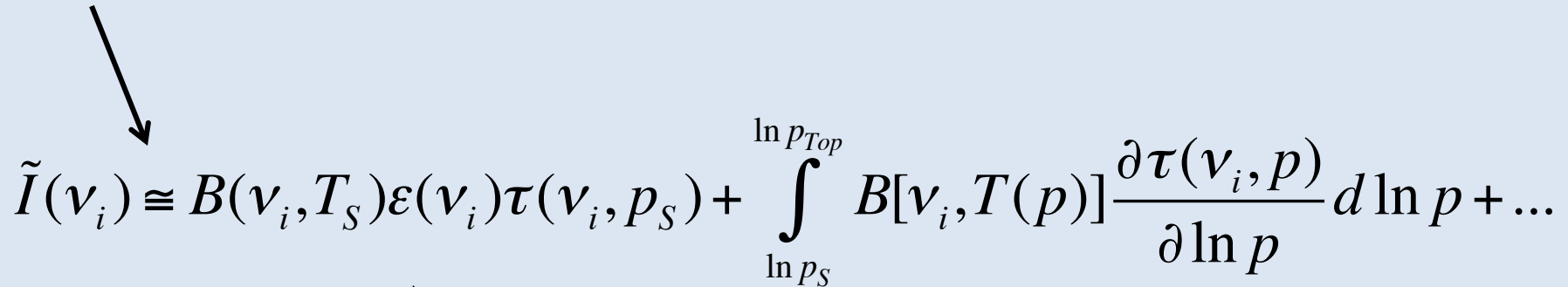
An Admission:
This 'equation' is not an equation.

Observed radiance

$$\tilde{I}(\nu_i) \cong B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) + \int\limits_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)]\frac{\partial \tau(\nu_i, p)}{\partial \ln p} d\ln p + ...$$

Calculated surface contribution

Calculated atmospheric contribution

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Retrieving internal parameters is a *minimization* problem.

- We know *observed* radiance
- Match these with *hypothesized* internal information like T_s, $T(p)$, etc.
  - Calculation requires a forward model.
  - Need to choose a cost function for the minimization, as here:

Observed radiance

$$\varepsilon = \min \left\| \tilde{I}(\nu_i) - B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) - \int\limits_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)] \frac{\partial \tau(\nu_i, p)}{\partial \ln p} d \ln p \right\|$$

Calculated surface contribution

Calculated atmospheric contribution

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One Approach: Statistical Retrievals

Tabulate simulated radiances for a wide range of conditions, then regress the observed radiances onto known states.

- **Advantages**
  - **Fast.**
  - **Simple.**

- **Disadvantages**
  - **Weak mathematical or physical justification.**
  - **Poor uncertainty propagation.**

Another Approach:
Physical Relaxation

Iterate this equation until ε is within acceptable limits.

$$\varepsilon = \min \left\| \tilde{I}(\nu_i) - B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) - \int\limits_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)]\frac{\partial \tau(\nu_i, p)}{\partial \ln p} d\ln p \right\|$$

- **Advantages:**
  - **Some physical justification**
  - **Computationally fast.**

- **Disadvantages**
  - **Physical justification is ad hoc.**
  - **Solution may have multiple minima.**
  - **Poor uncertainty propagation.**

Yet Another Approach: Optimal Estimation (Bayesian) Methods

- **Advantages:**
  - **Good mathematical foundation.**
  - **Incorporates prior information; explicitly handles error propagation and multiple minima.**

- **Disadvantages**
  - **Computationally expensive.**
  - **Require prior information, including a climatology.**
  - **'Some people treat it like a religion.' -Anonymous JPLer**
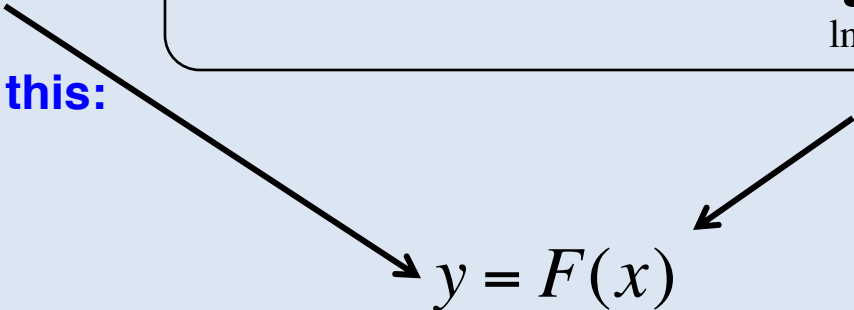
Optimal estimation is becoming the community standard, though not all instruments use it (e. g. AIRS currently uses a combined statistical and relaxation method).

Optimal Estimation:
Generalize the Inverse Problem

Reduce this:

$$\tilde{I}(v_i) \cong \left[B(v_i, T_S)\varepsilon(v_i)\tau(v_i, p_S) + \int_{\ln p_S}^{\ln p_{Top}} B[v_i, T(p)] \frac{\partial \tau(v_i, p)}{\partial \ln p} d\ln p \right]$$

to this:

$$y = F(x)$$

Where

x = vector of retrieved quantities $[T_s, T(p), \text{etc.}]$.

y = vector of observed radiances.

F = forward (radiance) model.

We want the inverse:

$$x = F^{-1}(y)$$

Optimal Estimation in a nutshell

Minimize this cost function:

$$\varepsilon = \min_{x}\left(\left\| y - F(x) \right\|^2_{S_n^{-1}} + \left\| x - x_c \right\|^2_{\Lambda} \right)$$

Where

x = retrieved state vector

y = observed radiance

F(x) = forward modeled radiance

S_n^{-1} = noise covariance matrix

x_c = first guess

Λ= constraint matrix.

Slide courtesy Bill Irion, JPL

'Shamelessly cribbed from *Worden et al., JGR, 109,* doi:10.1029/2004JD004522, 2004' -Irion

An Aside

- **The cost function is a matter of taste.**

- **Two examples shown today:**

$$\varepsilon = \min \left\| \tilde{I}(\nu_i) - B(\nu_i, T_S)\varepsilon(\nu_i)\tau(\nu_i, p_S) - \int\limits_{\ln p_S}^{\ln p_{Top}} B[\nu_i, T(p)]\frac{\partial\tau(\nu_i, p)}{\partial \ln p} d\ln p \right\|$$

$$\varepsilon = \min_{\mathrm{x}}\left(\left\|\mathrm{y} - \mathrm{F(x)}\right\|^2_{\mathrm{S_n^{-1}}} + \left\|\mathrm{x} - \mathrm{x_c}\right\|^2_{\Lambda}\right)$$

- **This is analogous to a choice of statistical characterization**
  - **Mean, mode, or median?**
  - **Standard deviation or interquartile range?**
  - **Chocolate or vanilla?**
  - **…**

Jacobians (Weighting Functions) and Gain

Jacobian - relates change in forward model F to change in "true" state, x.

$$K = \frac{\partial \mathrm{F}}{\partial \mathrm{x}} \quad \text{same as} \quad \frac{\partial \tau(\nu_i, p)}{\partial \ln p}$$

Gain - relates change in retrieved state, $\hat{\mathrm{x}}$, to forward model radiance, F.

S_n is the noise term $[\mathrm{nn}^T]$, and Λ is the constraint matrix (usually prior covariance^{-1}).

$$G = \frac{\partial \hat{\mathrm{x}}}{\partial \mathrm{F}} = \left(K^T S_n^{-1} K + \Lambda \right)^{-1} K^T S_n^{-1}$$

Slide courtesy Bill Irion, JPL

'Shamelessly cribbed from *Worden et al., JGR, 109,* doi:10.1029/2004JD004522, 2004' -Irion

Averaging Kernels and Information Content

Averaging kernel - relates change in retrieved state, $\hat{x}$, to true state, x.

$$A = \frac{\partial \hat{x}}{\partial x} = \frac{\partial \hat{x}}{\partial F}\frac{\partial F}{\partial x} = GK$$

Final retrieval, from the averaging kernel, smooths the difference between the true state, x, and the a priori, x_a.

$$\hat{x} = x_a + A(x - x_a) + Gn$$

The trace of the averaging kernel matrix is the number of degrees of freedom in the retrieval.
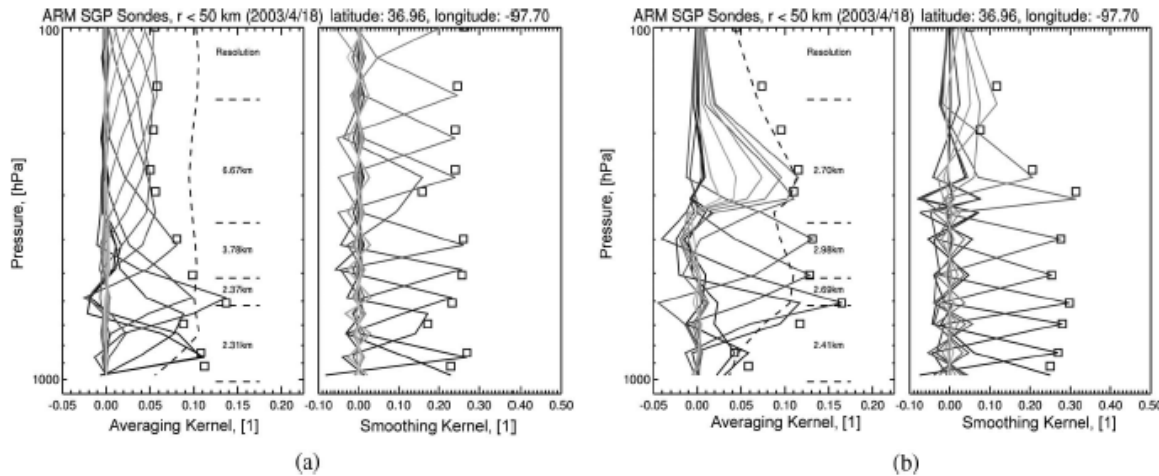
AIRS Averaging Kernels

Fig. 4. Example of effective averaging kernels $\mathbf{F\Phi F}^{+}$ and smoothing kernels $\mathbf{FF}^{+}$ for a midlatitude case over the ARM site SGP on April 23, 2003.
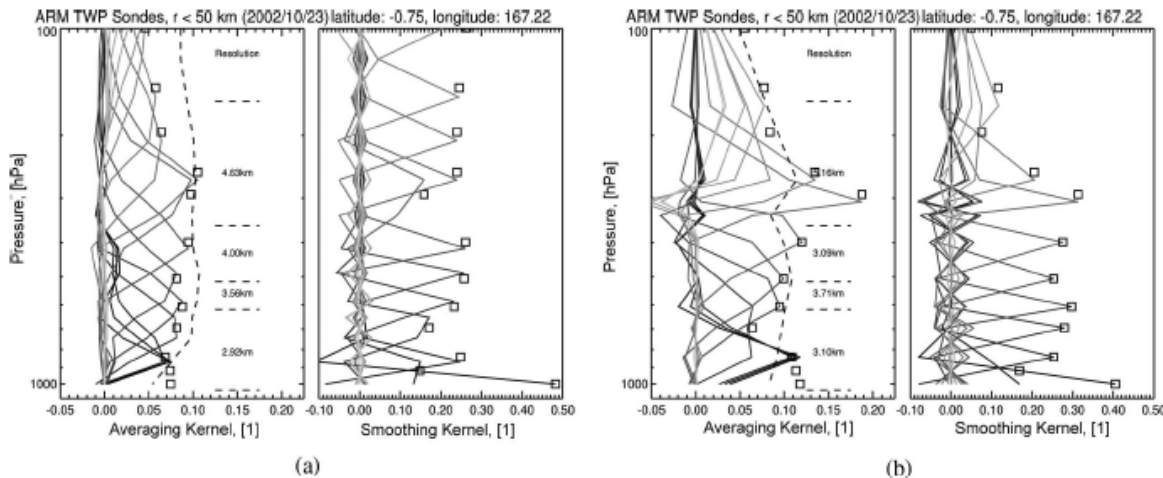
Fig. 5. Example of effective averaging kernels $\mathbf{F\Phi F}^{+}$ and smoothing kernels $\mathbf{FF}^{+}$ for a tropical case over the ARM site TWP on October 23, 2002.
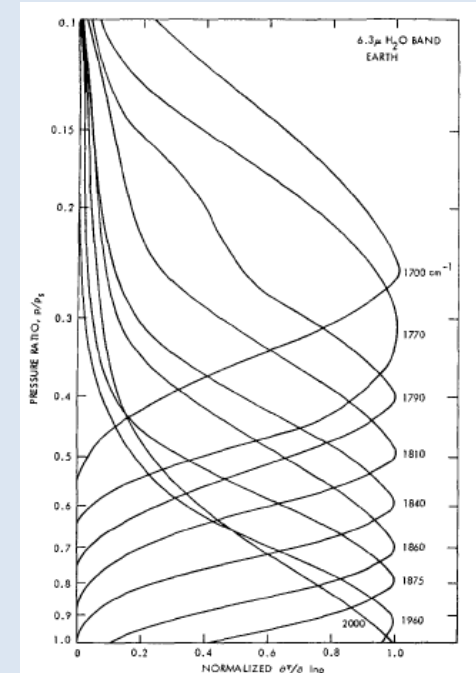
FIG. 1. Normalized weighting functions $(d\tau/d \ln p)$ for the selected set of nine sounding frequencies computed for an instrumental slit function of 5 cm^{-1} (see text).

Compare weighting functions

From: Maddy and Barnet (2008), Vertical resolution estimates in version 5 of AIRS operational retrievals, TGARS.

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Finally: The Null Space

- **The set of *unobservable states*. Examples:**
  - **Vertical structure smaller than averaging kernel scales.**
  - **Scenes obscured by clouds (infrared) or precipitation (microwave).**

Understanding the null space is a fundamental challenge of atmospheric remote sensing. Auxiliary information is needed to define it.

Some Thoughts on the Future

- *Interpretation of retrieved quantities remains a challenge*
  - Though less daunting than observed (cloudy) radiances.
  - We have a lot of both radiances and retrievals.

- *Retrieval methodologies are still relatively immature*
  - Statistical and relaxation methods are near their limit of usefulness for characterizing errors.
  - Optimal estimation methods have not been widely applied to the very large data sets from NASA facility instruments (MODIS and AIRS).
  - *Retrieving cloud state with other properties is the main challenge.*

- *Model assimilation of cloud-affected radiances for T and q is a BIG challenge.*

References

- **Books:**
  - <u>Good intro:</u> Menke, 1989, Geophysical Data Analysis: Discrete Inverse Theory, Academic, New York.
  - <u>General</u> theory: R. L. Parker, 1994, Geophysical Inverse Theory, Princeton
  - <u>Theoretical with atmospheric emphasis:</u> C. D. Rodger, 2000, Inverse Methods for Atmospheres: Theory and Practice, World Scientific, 2008 reprinting.
  - <u>Intro and instrumentation:</u> S. Kidder and T. Vonder Haar, 1994, Satellite Meteorology: An Introduction, Academic Press.

- **Papers:**
  - Chahine, M. T., 1970, J. Atmos. Sci.
  - Smith, W., 1970, Applied Optics.
  - Worden et al., 2004, JGR.
  - Maddy and Barnet, 2008, TGARS.
  - Gordley and Russel, Appl. Optics, 1981.

Supplementary Slides

Spectral Bands Determined by Radiative Transfer Physics *and Technology*

- Visible
  - Very high horizontal resolution.
  - Low atmospheric opacities => applicable to aerosol, clouds and surface.
  - Calibration to better than 10% is difficult.

- Infrared
  - Moderate horizontal resolution (~10 km; higher possible).
  - High spectral resolution.
  - Can be calibrated to ~0.1 K RMSE brightness temperature.
  - Mixed atmospheric opacities => information about vertical structure, clouds, and surface.
  - Cannot sound through cloud optical depths ≥1.

Spectral Bands Determined by Radiative Transfer Physics and Technology (continued)

- Microwave
  - Mixed atmospheric opacities (like infrared).
  - Small cloud opacities
    - Can sound into non-precipitating clouds.
  - Lower spectral and spatial resolution because of receiver and antenna costs
    - Limited spectral resolution translates to limited vertical information.

Note: Resolution and sensitivity for all wavelengths are closely tied to the *observational null space*.